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Gender and Age Influence on Energy Consumption in A Selected Malaysian Office Building

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Abstract
Due to the fact that the majority of large buildings are being built in densely populated urban areas, Malaysian buildings use more energy per square metre of floor space than those in the majority of other nations. The researcher and intervention designer will be able to determine the impact of each social parameter on the building energy performance with the aid of their understanding of how and which social parameters contribute to building energy performance. The energy consumption profiles may include gender and age-related variables. When taking into account the correlation between age and energy consumption, this study sheds light on energy consumption and gender. The purpose of this study is to determine the connection between gender, age, and the amount of energy used in an office building. After that, it will go into how this group may be a springboard for fresh, energy-saving techniques that will ultimately benefit everyone. Using a combination of statistical and neural network methods, 1,116 samples from 13 office building locations across 150-day periods were assessed. Large amounts of data are difficult to evaluate using simply traditional statistical approaches, thus neural networks are employed to model and analyse these data sets. The study's findings imply that gender and age play a role in how efficiently a building uses energy. The findings show that women spend much more energy than men, and that the most significant age groups for energy consumption are those under 30 and those between 41 and 50 years old.
Keywords: Energy Consumption, Gender Impact on Energy, Age Impact on Energy, Neural Network.

Introduction

Building energy performance in different countries varies due to factors such as building codes, standards, laws and regulations, appliances used, building occupant behaviour and several other factors which vary greatly from country to country (Delzendeh et al., 2017). An organization needs to understand these factors and address them through engineering and energy systems design for the optimum performance of the building energy usage (Blok et al., 2007).

There are various ways to approach the idea of building performance. It will be clear that such factors must play a crucial role in the theoretical underpinnings of architecture. There have been numerous attempts to create descriptive and prescriptive theories, and these have a tendency to focus on particular aspects of the structure (Baird et al., 2018). Employing physics-based models like Energy Plus is an example of building energy simulation tools have been extensively used to research and assess building energy performance.(Deng, Fannon, and Eckelman 2018) Although obtaining very specific architectural information, such as specific space features, might be challenging, realistic simulation is frequently necessary (Nguyen et al., 2014).

This study will address the result using a realistic simulation that based on Artificial Neural Network (ANN). The modelling of complicated and nonlinear patterns is a notable use of artificial neural network (ANN) approaches. The algorithm's training process is comparable to the structure of human brains, which have a set number of layers and neurons. Input, output, and hidden layers are the components of a typical ANN design. Although the output layer produces the finished product, the input layer collects all input values. Because to interference between input and output neurons, the presence of hidden layer(s) essentially ensures that ANN models have non-linear relationships (Simon Haykin (McMaster University et al., 2005).

The Artificial neural networks (ANNs) will identify the pattern which developed a choice (Juan and Valdecantos, 2022). Using numerical models to solve statistical engineering problems is the most common approach. However, the development of machine learning has shown that ANNs are a very good alternative to this traditional approach and even give better results, particularly when the problem is random and contains non-linear patterns (Fan et al., 2021; Maier and Dandy, 2000). ANNs are better suited for problems with a random distribution of variables than traditional statistical models since they lack strict guiding principles that set them apart from the latter (Maier and Dandy, 2000). Further support is provided by the interpretability of artificial neural networks, which is essential in many fields, including engineering and medicine, due to the robustness of the models (Guo et al., 2019; Li et al., 2021; Yu and Carrillo, 2019).

Literature Review

Building energy performance refers to the full range of factors that affect the performance of a building, including design, planning and construction. Various factors could have a positive or negative impact on energy efficiency. Generally, passive and active technical approaches are adopted for building energy performance. Passive technical components include daylight harvesting, solar shading and glazing properties. Active technical components include electrical appliances and lighting (Tang and Chin, 2013; Noor, 2016).

From a social standpoint, social demographics, psychological variables, and technological aspects of the buildings may all have an impact on how energy-efficient a building is. Age, gender, education level, employment status, social economic status, income level, household features, building characteristics, and geology characteristics are examples of social elements (Hess and Sovacool, 2020).

It's crucial to comprehend how and which societal factors affect how efficiently a structure uses its energy. The researcher and intervention designer will be assisted in determining the influence of each social parameter on the building's energy efficiency by the social parameter's contribution. The majority of studies in this field often focused on occupancy as a variable rather than breaking it down into various distinct social parameter variables and, sporadically, technical parameters. Instead of breaking down occupancy into various distinct social parameter variables and occasionally as a technical parameter, these studies typically focused on occupancy as a variable. in additional, usually the study on the impacts of building occupancy, a stochastic model was used (Jang and Kang, 2016).

However according to recent studies, there is a significant difference between a building's expected and actual energy use. Several studies have agreed that the primary causes of the discrepancy between expected and actual building energy performance are human behaviour and tenant preferences (social parameter) (Martinaitis et al., 2015; Yang et al., 2016; Calì et al., 2016).

Analysis of energy consumption has looked at the causes, projections, and modifications in occupant behaviour. Social factors including age and gender, among others, have been investigated to explain why people's energy consumption and energy saving behaviour vary. The social parameter is best defined by the eight social parameters that are the best energy performance predictors and/or parameters (Olli et al., 2001). Figure 1 shows integrative conceptualization of the various individual (socio-demographic and psychological) and situational (contextual and structural) factors that associate with energy performance.

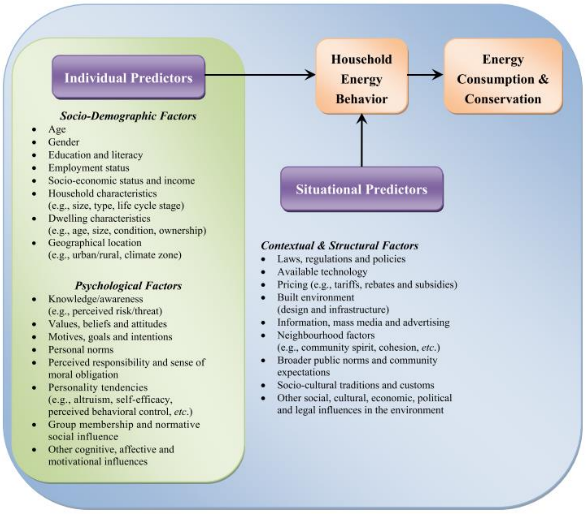


Figure 1: Integrative conceptualization of the various individual (socio-demographic and psychological) and situational (contextual and structural) factors that associate with energy performance (Olli et al., 2001).

To associate social factors with building energy performance, several sociological studies have been conducted in the past. There are several societal factors stated. Building energy performance is significantly influenced by factors including gender, age, education, proximity to other people, urban location, employment, income, political orientation, and ecological attitude (Olli et al., 2001).

While Hines et al. focus on educational level, Income, Economic orientation, Age and Gender (Hines et al., 1987). Marcos used Gender, Age and conservation behaviour as their social parameter (Marcos, 2009). Table 1 describe the social research related to building energy performance, method use and other attributes that are related to the research.

Table 1
Social research Related to Energy and Research Attributes

Source	Data Type*	No of Sample	Social Parameter use	Method use
(Olli et al. 2001)	SV	5686	Gender, Age, Education, Living Proximity, Urban Location, Employment, Income, Politic Orientation, Ecological Attitude	- 5-point Likert scale -Correlation Pattern - Multiple Regression
(Hines et al. 1987)	SV	315	Education Level, Income, Economic Orientation, Age, Gender	-Meta-analysis
(Marcos 2009)	SV	3338	Gender, Age, Conservation behaviour	- 5-point Likert scale -Pearson correlation -Regression

*Data Type: A= Actual, S = Simulation, SV=Survey

Space Standard Occupancy Load

The Uniform Building By-law of 1984 (UBBL 1984) is the rule that governs the specifications for all structures in Malaysia. This standard is used to define the space standards for computing occupancy loads. The net floor area or space given to the use shall be divided by the square metre per occupant to yield the maximum office occupancy load authorised. According to the UBBL of 1984, the number of installed fixed chairs shall be used to calculate the occupancy load of the office area.

Research Framework

Based on the common social parameter used on Table 1 which are gender and age. This study is to comprehend how age and gender influence office building energy consumption. Data analysis will combine statistical and neural network techniques, with the former being used to identify links between energy use and gender while taking into consideration its association with age.

In order to determine how varied gender and ages effect energy consumption, artificial neural networks are used in the research's examination of space occupancy load. The artificial neural network is capable of making predictions based on actual data for the occupancy value for segregated gender and age as well as the occupancy value for off-range variables value.

Material and Method

This research studied the effect of social parameters on energy consumption in a large office building. Neural networks are used to model and analyse large quantities of data, which are difficult to be analysed using only classical statistical methods such as correlation and regression analysis. The neural network with back propagation is applied to obtain an accurate prediction of the energy consumption model.

Data Collection Samples

A methodical data collection process that used 484 individuals over the course of 150 days to acquire primary data. The source sample data were collected from 13 locations with sample sizes, purposes, and meteorological characteristics that were similar to each other. Every employee's gender and age background are tabulated.

The samples variable parameter, age is divided into four categories which are below 30, 31 – 40, 41-50 and above 50 years old. The other parameter is the gender, male and female. The daily total occupancy is determined using the gender and age background of each floor's attendants. Each access door has a magnetic door sensor station that records the attendant. Data loggers are used to track energy consumption in each electrical riser on each location.

Data Pre-processing

Raw data logger and Magnetic Door Station Main data source was processed using Microsoft Excel Data Vlookup, which screened and chose the appropriate data. A suitable format for training an AI model will be created by combining, cleaning, normalizing, and transforming each daily sample location's data.

Data Analysis

Data analysis and model development are based on analysis using SPSS Statistical software. Multiple Regression is the method used for in data Analysis. In addition, data testing and validation are based on Neural Network Fitting MatLab analysis. The setting for Neural Network Fitting is based on 70% or 782 training samples, 15% or 167 validation samples and 15% or 167 testing samples. Figure 2 shows the Neural Network Diagram. Result of the training is based on Bayesian Regularization as Training Algorithm.

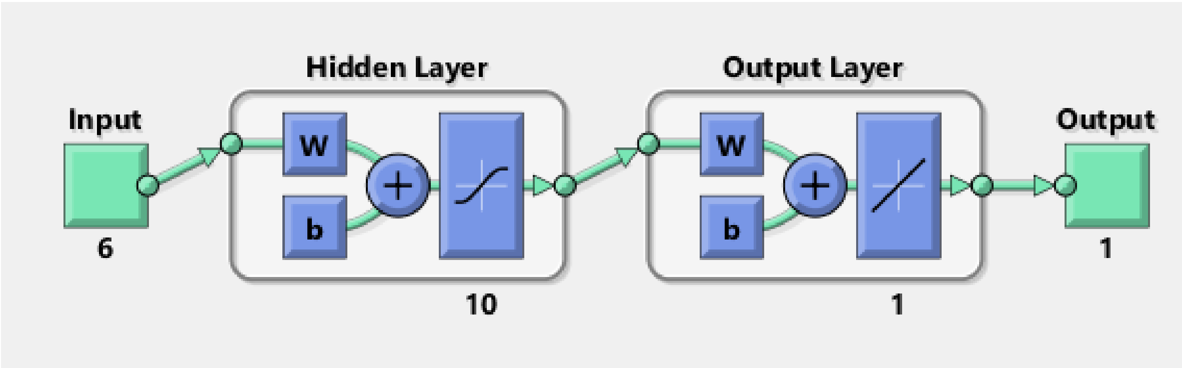


Figure 2 : Neural Network Diagram

Result of The Emperical Research

The result of samples descriptive statistics shows that 1,116 samples has been analysed. The respective mean value and standard deviation are given in Table 2. The samples that age more than 50 is the least compared to other age group and male samples mean is 14.6 which is more than female samples.

Table 2

Descriptive Statistics

	Mean	Std. Deviation	N
Below_30	6.5529	5.20864	1116
Age31to40	8.0197	6.27341	1116
Age41to50	6.8244	5.12810	1116
Male	14.6174	11.43418	1116
Female	10.9265	9.47236	1116
EnergyUse	48.7398	40.56864	1116

Based on Uniform Building by-law 1984 (UBBL 1984) which discussed before, the space standards for calculating occupancy loads is tabulated in Table 3. Table 3 summarized the maximum Space Occupancy Load in the sample location.

Table 3
Space Occupancy Load

All Categories	Sample Net Floor Area for occupancy (m^2)	Working Area Size (m^2)	Maximum Space Occupancy Loads
Maximum Occupancy	602	2.0	301

Table 4 Indicates that the adjusted R Square is 0.411 or 41.1%. The result indicates that 41.1% of the samples are explained by the independent variable. Whereas, the significant value which less than 0.05 or 5%, the result shows that null hypothesis is rejected. This proven that there are statically significant differences cause by the independent variables to the dependent variable.

Table 4
Model Summary

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.644[a]	.414	.411	31.13426	.414	130.687	6	1109	.000

a. Predictors: (Constant), Female, Male, Above_50, Age41to50, Below_30, Age31to40

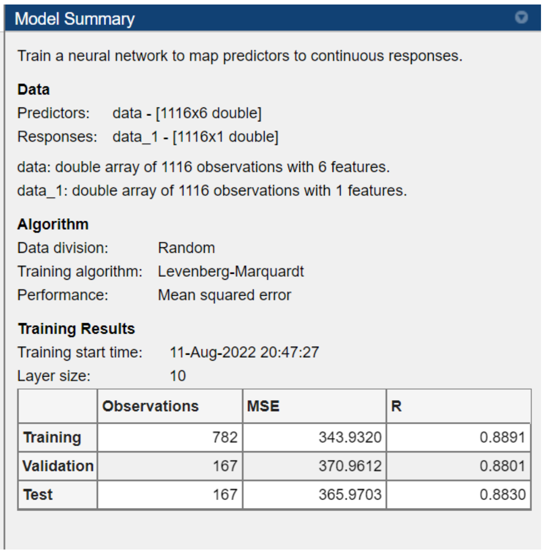
Using the Pearson Correlation, the relationship between dependent variable and independent variables is summarized in Table 5. The result indicates that significant level of all the variable is less than 0.05 or 5%. This shows that there are significant differences cause by each variable. The age group of 41 to 50 years old have the highest correlation related to the energy consumption pattern. Generally, the age group below 50 years old have more correlation with energy consumption compare to those above 50 years old.

Table 4
Pearson Correlations

Correlations

		EnergyUse	Below_30	Age31to40	Age41to50	Above_50	Male	Female
Pearson Correlation	EnergyUse	1.000	.413	.381	.532	.296	.427	.377
	Below_30	.413	1.000	.910	.663	.608	.763	.746
	Age31to40	.381	.910	1.000	.724	.687	.840	.741
	Age41to50	.532	.663	.724	1.000	.821	.707	.766
	Above_50	.296	.608	.687	.821	1.000	.755	.584
	Male	.427	.763	.840	.707	.755	1.000	.412
	Female	.377	.746	.741	.766	.584	.412	1.000
Sig. (1-tailed)	EnergyUse	.	.000	.000	.000	.000	.000	.000
	Below_30	.000	.	.000	.000	.000	.000	.000
	Age31to40	.000	.000	.	.000	.000	.000	.000
	Age41to50	.000	.000	.000	.	.000	.000	.000
	Above_50	.000	.000	.000	.000	.	.000	.000
	Male	.000	.000	.000	.000	.000	.	.000
	Female	.000	.000	.000	.000	.000	.000	.
N	EnergyUse	1116	1116	1116	1116	1116	1116	1116
	Below_30	1116	1116	1116	1116	1116	1116	1116
	Age31to40	1116	1116	1116	1116	1116	1116	1116
	Age41to50	1116	1116	1116	1116	1116	1116	1116
	Above_50	1116	1116	1116	1116	1116	1116	1116
	Male	1116	1116	1116	1116	1116	1116	1116
	Female	1116	1116	1116	1116	1116	1116	1116

Due to the limitation of statistical method when handling more than two degrees of freedom, model Neural Network method is used as a tool for data fitting. This model summary result using Levenberg-Marquardt is shown in Figure 4. The result indicates the satisfying R value for training, validation, testing of 0.8891, 0.8801 and 0.8830 respectively.


Model Summary

Train a neural network to map predictors to continuous responses.

Data
Predictors: data - [1116x6 double]
Responses: data_1 - [1116x1 double]

data: double array of 1116 observations with 6 features.
data_1: double array of 1116 observations with 1 features.

Algorithm
Data division: Random
Training algorithm: Levenberg-Marquardt
Performance: Mean squared error

Training Results
Training start time: 11-Aug-2022 20:47:27
Layer size: 10

	Observations	MSE	R
Training	782	343.9320	0.8891
Validation	167	370.9612	0.8801
Test	167	365.9703	0.8830

Figure 3: Neural Network Model Summary

Further analysis in Figure 4 shows that the Mean-Squares-Error of the of Training, Validation and Testing value is decreasing inverse exponentially. At epoch 32, Training, Validation and Testing values are approximately similar.

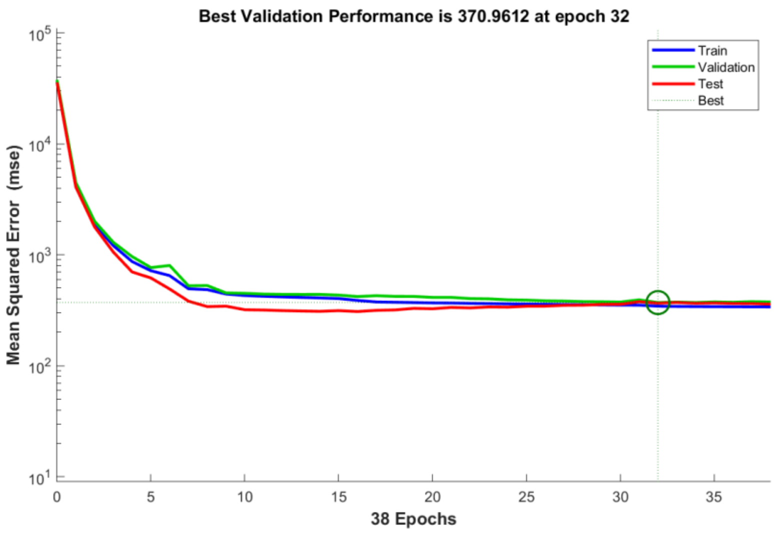


Figure 4: Neural Network Performance Validation

Figure 5 shows present of data related to the Age Range Parameter and energy consumption using a Matlab Plot Graph. In contrast to the energy consumption, the results demonstrate a continuous consistency in the total Age Range Parameter. As indicated in Figure 6, additional study was done to investigate the connection between a particular Age Range Parameter and energy consumption. Although it is still not able to definitively pinpoint the causes of this fluctuation, the results imply that the data's homogeneity is inconsistent.

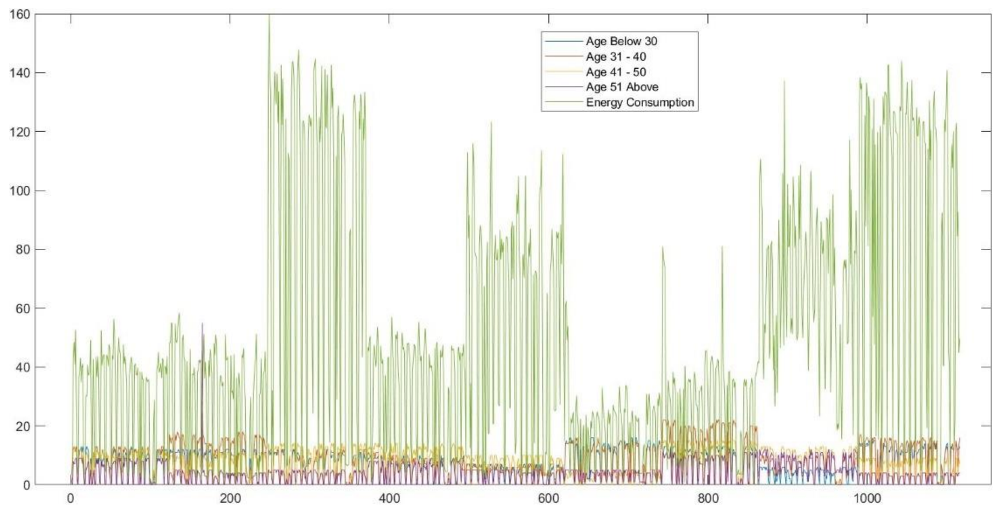
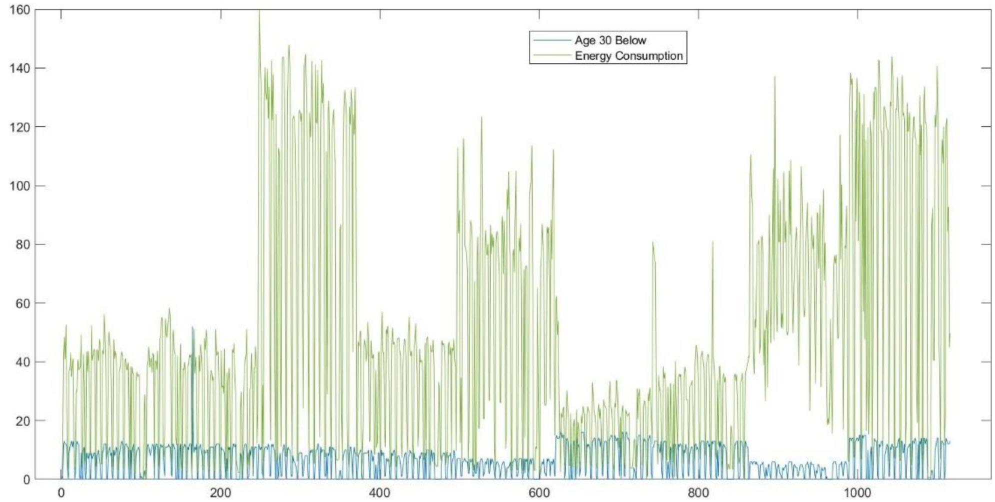
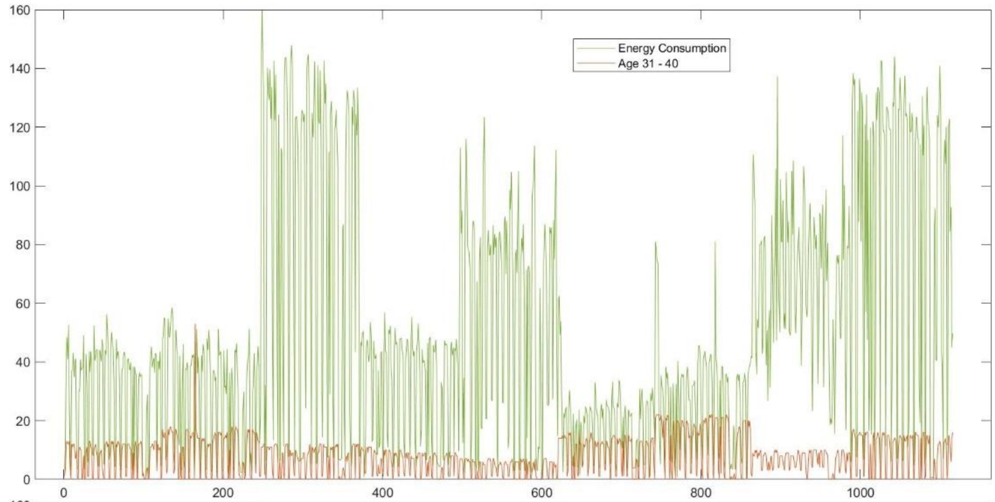
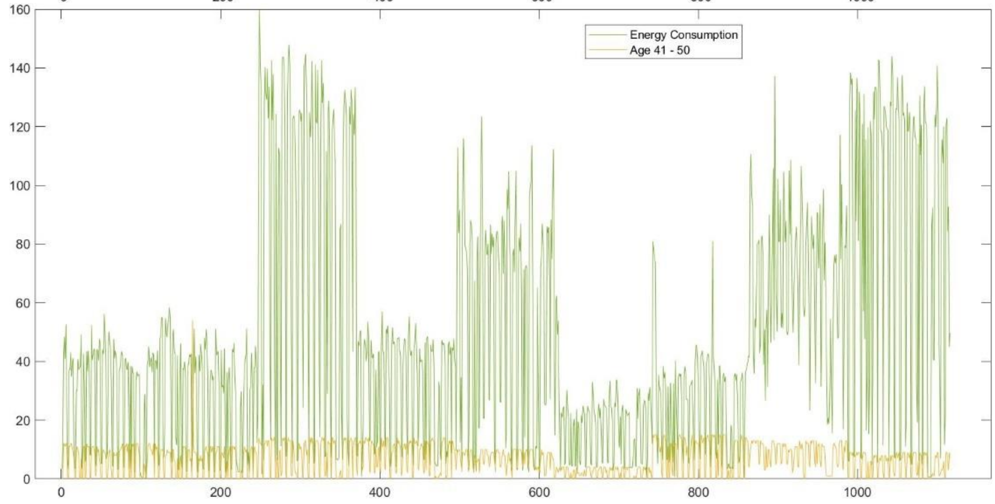


Figure 5: Matlab Plot Graph on Overall Age Range Parameter and Energy Consumption


Age 30 Below
Energy Consumption


Energy Consumption
Age 31 - 40


Energy Consumption
Age 41 - 50

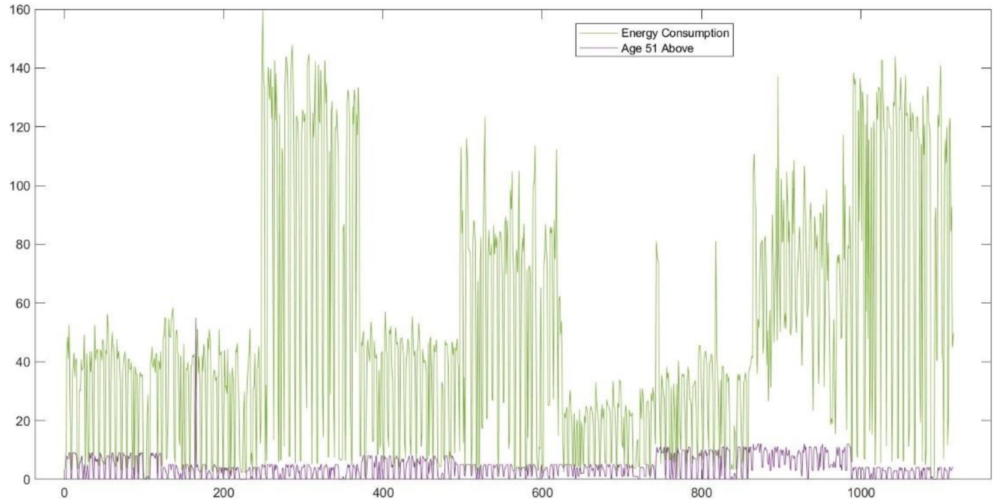


Figure 6: Matlab Plot Graph on Specific Age Range Parameter and Energy Consumption

Using a Matlab Plot Graph, Figure 7 displays data relating to the overall gender parameter and energy consumption. The findings show that the total gender parameter is inconsistent, in contrast to energy consumption. Further research was conducted, as shown in Figure 8, to look into the relationship between male and female gender and energy use. The findings imply that the data's homogeneity is inconsistent, even though it is still unable to conclusively identify the reasons for this variation.

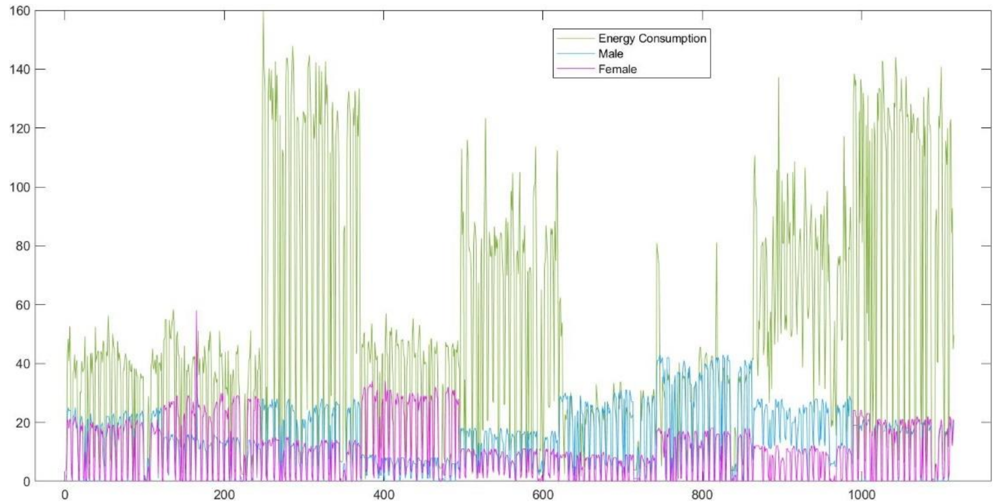


Figure 7: Matlab Plot Graph on overall gender parameter and Energy Consumption

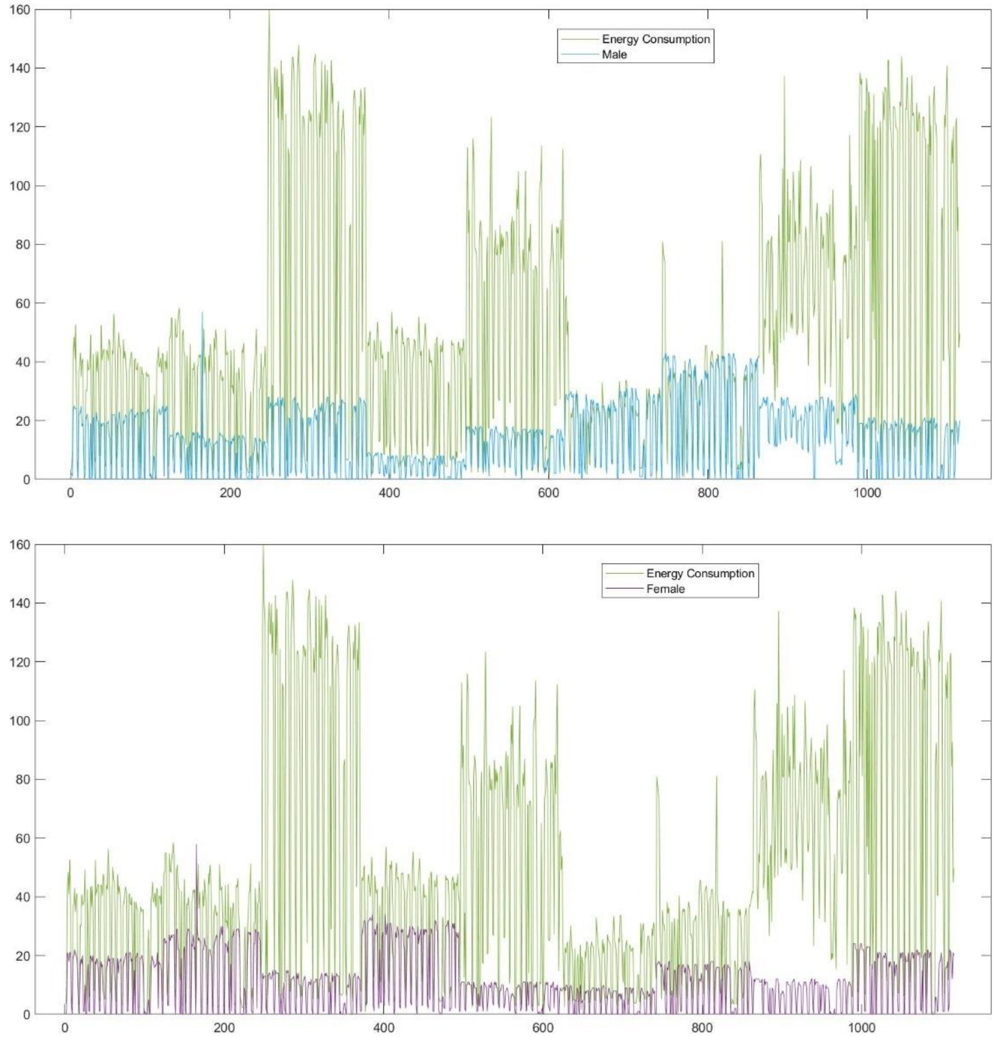


Figure 8: Matlab Plot Graph on Specific Gender Parameter and Energy Consumption

The effect of age and gender on energy consumption was shown through the use of Matlab Bar Plotting. A trustworthy assessment of the impact value was hampered by the separation of these parameters and the existence of noise in the data. Hence, to acquire a more thorough understanding of the impact of age and gender characteristics on energy consumption, a comparison between the collected data and a model would be required. An artificial neural network in Matlab was used to build a model from sample data. This method can be used to forecast and comprehend the values of data related to various age and gender characteristics. The Matlab Neural Network Fitting on Regression Plotting is displayed in Figure 9.

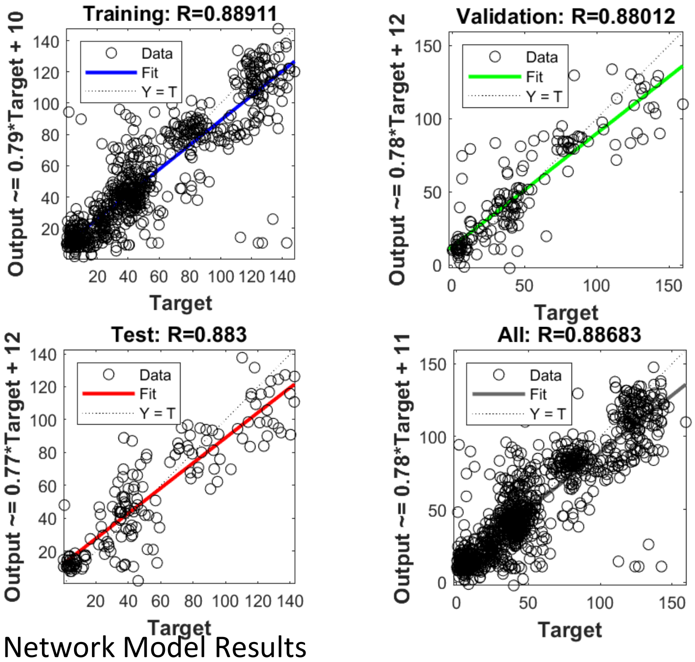


Figure 9: Neural Network Model Results

The Regression Plot in Figure 9 indicates that few samples are observed tabulated on the outer region. This might be due to few isolated issues which cause irregular working routine that interrupting daily routine. These isolated issues might cause less energy consumption and higher energy consumption. Activities that need occupant to attend function outside office during office hours might cause the decrease in energy consumption value, whereas, activities such as meetings increase energy consumption.

A comparison between the Model Plotting Result and Real Model Plotting Result was carried out using Artificial Neural Networks (ANNs). The obtained information was then examined to find similarities between the models. To forecast energy consumption in office buildings, the model created in this work combines high-performance actual data models and computer simulation models. The findings of this investigation are presented in Figure 10.

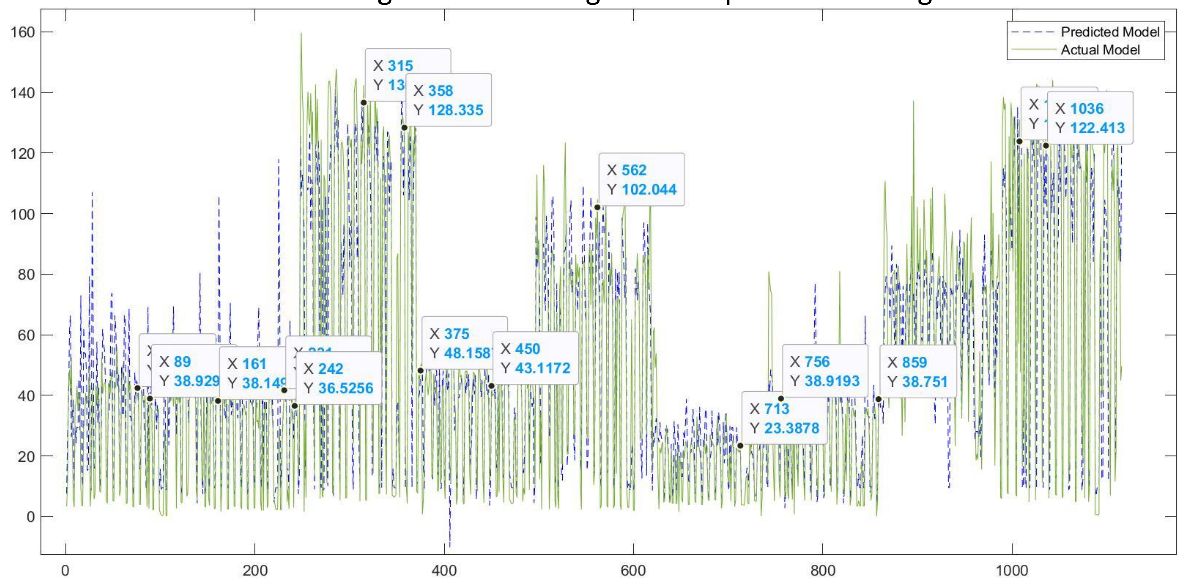


Figure 10: Obtained Model Plotting Result and Actual Model Plotting Result

The 15 matching points that show similarities between the models are calculated based on Figure 10. These values are compared to the actual data in order to determine the values for the age range and gender variables at each of the 15 matching points. Using an acquired model from artificial neural networks, the energy consumption value during maximum Space Occupancy Load as shown in Table 3 and 15 matching points educational level is calculated (ANNs). The obtained energy consumption value is summarised in Table 5.

Table 5
Variable impact on Predicted Neural Network Model

Test Condition	Social Demographic - Independent Variable						Dependent Variable
	Age				Gender		Energy Consumption retrieved from Predicted Model
	Below 30	31~40	41~50	above 51	Male	Female	
	V1	V2	V3	V4	V5	V6	
1 (Point 76)	13	12	11	8	24	20	42.4250
2 (Point 89)	9	11	12	8	21	19	38.9298
3 (Point 161)	12	15	10	4	14	27	38.1490
4 (Point 231)	12	17	10	3	14	28	41.6936
5 (Point 242)	10	16	10	4	12	28	36.5256
6 (Point 315)	10	10	14	4	26	12	136.5837
7 (Point 358)	10	9	13	5	25	12	128.3347
8 (Point 375)	9	10	13	8	9	31	48.1587
9 (Point 450)	8	9	10	8	6	29	43.1172
10 (Point 562)	4	6	9	4	16	7	102.0437
11 (Point 713)	13	14	4	5	27	9	23.3878
12 (Point 756)	12	21	14	11	42	16	38.9193
13 (Point 859)	13	20	14	11	40	18	38.7510
14 (Point 1008)	15	16	9	4	21	23	123.8301
15 (Point 1036)	11	15	6	4	18	18	122.4126
Min V1 & V5	1	0	0	0	1	0	8.9733
Min V1 & V6	1	0	0	0	0	1	15.1281
Min V2 & V5	0	1	0	0	1	0	7.4408
Min V2 & V6	0	1	0	0	0	1	15.7954
Min V3 & V5	0	0	1	0	1	0	8.5451
Min V3 & V6	0	0	1	0	0	1	12.3779
Min V4 & V5	0	0	0	1	1	0	6.6852
Min V4 & V6	0	0	0	1	0	1	14.1796
Max V1 & V5	602	0	0	0	602	0	207.6181
Max V1 & V6	602	0	0	0	0	602	317.8772
Max V2 & V5	0	602	0	0	602	0	125.6350
Max V2 & V6	0	602	0	0	0	602	121.4071
Max V3 & V5	0	0	602	0	602	0	104.0305
Max V3 & V6	0	0	602	0	0	602	235.9015
Max V4 & V5	0	0	0	602	602	0	22.2201
Max V4 & V6	0	0	0	602	0	602	23.5089

A comparative analysis was done using Table 5's 15 matching point result value. The matching point result cannot reveal any appreciable disparities. Finding the impact of gender and age effluent on each tested point was hampered by uniformity within each tested point.
Values of 8.9733kWh, 7.4408kWh, 8.5451kWh, and 6.6852kWh for males, respectively, are obtained from the analysis of minimal independent variable data as classified by gender. As opposed to 12.3779kWh, 15.1281kWh, 15.7954kWh, and 14.1796kWh for women. The data shows that women consume 44% to 112% more energy regardless of age range. The least gender different is for age 41 – 50 years old. The minimum value data revealed that gender had a considerable impact while age range gives less significant impact on energy consumption.
The most notable influence on gender can be shown for male and female aged 41–50 years old with variances of 127% using the maximum Space Occupancy Load variable impact data. Another significant value for age parameter, however, can only be seen for age groups under 30, which results in high values of 43% and 119% deviations from the overall maximum Space Occupancy Load average for energy consumption.
According to the results of the variable effect analysis utilising minimal value occupancy, women in general have a significant impact on the office building's energy consumption. Yet, during periods of high occupancy, women under the age of 30 and women aged 41 to 50 have the greatest differences from men.

Conclusion

Therefore, the research will use a neural network approach. This approach enables data analysis and the development of statistical models. Since various demographic categories were used in each nation and no comparable data from another nation was available, overall results varied. This study finding has comprehend how age and gender influence office building energy consumption.
In order to compare actual data and the anticipated data model, neural networks were used in the research. According to the findings, female gender categories use more energy than male gender categories do. Also, the age groups with the highest energy usage were found to be women under the age of 30 and those between the ages of 41 and 51.
In this paper, we have explored in-depth the factors that impact energy consumption in a Malaysian office building. Based on this study contribution, simple action such as work from home group segmentation and area segmentation can be a way to optimize energy usage. Furthermore, because they shed light on how energy conservation should be done in an office building under varied conditions, these findings could be helpful for future research.
Yet, further research is needed on a few related issues because women in Malaysian culture frequently engage in "pot luck" gatherings and other food-related activities that require additional energy consumption. Also, throughout the course of this investigation, the utilization of "nice to have" gadgets like air conditioners, personal freezers, and air purifiers was noted.

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